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A Risk Management Approach to Business Process Design

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Design of Risk Management Strategies in Business Processes

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Abstract

With the development of such technologies as the Business Process Execution Language, a business-process-centric approach to the design of information systems has emerged. This approach calls for the modeling and design of the business process, both to document it as well as to analyze its risk characteristics. In this paper, we introduce a mathematical model to analyze the risk characteristics of business processes using its graph-theoretic structure. This focus on risk has been driven by recent legislative mandates, including the Sarbanes-Oxley Act on the integrity and reliability of the data reported in the financial statements, as well as the reliability and documentation of the information systems that produced those data. Our methodology considers the structural aspects of a process with respect to error generation, propagation, and risk mitigation. It finds cost-effective ways of embedding control procedures in the process that mitigate such risk exposure to meet desired risk thresholds. Our methodology lends itself to implementation within process modeling workbenches that are offered by leading software vendors. We illustrate our work through a case study regarding the order fulfillment process in a functioning online pharmacy.

1 Introduction

The importance of well designed business processes (BP) in organizations has long been recognized (Malone et al., 1999; Anupindi et al., 2005). Recently, mandates such as the Sarbanes-Oxley Act have led to a focus on documentation and analysis of the risk characteristics of processes (Krishnan et al., 2005). For example, according to *CFO* magazine, "Experts estimate that anywhere from 10 percent to 30 percent of the data flowing through corporate systems is bad..." (Goff, 2003, pp. 97–98). The Sarbanes-Oxley Act requires a firm's CEO and CFO to certify the reliability of the data reported in the financial statements, as well as the reliability and documentation of the information system that produced those data (Pasley, 2002). Similar concerns about data errors arise in other sectors, like the healthcare industry, in which patient safety has been a major concern following a widely publicized report from the *National Academy Press* (Kohn et al., 2000).

In this paper, we propose an approach to BP design that incorporates risk management. The approach employs decision theoretic methodology to analyze the risks associated with errors in the information flow used and generated by a business process. The method accounts for process structure in error generation, propagation, and mitigation, and is designed to determine the optimal manner in which controls – procedures that can find and fix errors – can be embedded in the business process at the task level to mitigate risk. Our objective is to develop a well-founded, quantitative approach to risk assessment and mitigation, which can be implemented and deployed as part of a tool kit or workbench (e.g., IBM WebSphere Process Modeler) to facilitate an iterative approach to process-centric analysis and design. The results from tests conducted using synthetic data from various BP structures show that our model minimizes both the mean and the variance of the risk distribution.

The literature on business processes is large and diverse in the Information Systems field (Basu and Kumar, 2002; van der Aalst, 2002; Kumar and Zhao, 2002; van der Aalst et al., 2003; Chakraborty and Lei, 2004). However, seldom has research studied BP design problems from the risk management perspective in such a way that accounts for the errors introduced by the process. Krishnan et al. (2005) developed a formal, task-level, process-oriented ontology of an accounting information system. We extend their work by modeling the characteristics of information flow and errors at the level of information transformation processes along with the effectiveness and cost of the controls designed to detect and correct errors. This enables assessment of the risk associated with data errors and development of optimal control strategies that mitigate risks while minimizing cost. As a result, this study contributes to the literature on ex-ante risk-based process design, as well as ex-post risk assessments of existing processes and control models. Since the methods proposed can be implemented in process modeling software (e.g., IBM Business Integration Modeler), it has the potential to be incorporated into tools for business process design.

The remainder of the paper is organized as follows: Section 2 surveys relevant work; Section 3 presents the models for transforming BP into directed graphs with attributes; Section 4 proposes a hierarchical probabilistic model of error distribution and propagation through the process graph; Section 5 illustrates the business control procedures and their roles in risk mitigation; Section 6 assesses the error associated risks, and proposes three optimization-based approaches to tradeoff the cost of applying controls and the reduction in risks brought about by the use of controls. We illustrate our model through the order fulfillment process in an online pharmacy in Section 7, and conclude in Section 8.

2 Relevant Work

We briefly survey in this section relevant work in organization, accounting, and information systems literature, and describe how our work incorporates key concepts from this literature to develop a quantitative risk estimation and management method for business process design.

Literature On Business Process (BP) Design and Analysis The literature on business processes is large and diverse from the organizational (Born, 1994; Hammer and Champy, 1993) and information systems perspectives.(Guha, 1997; Grant, 2002; Mansar and Reijers, 2005) Singhal et al. (1988) discussed the computational and organizational issues in BP design, and argued that the compatibility among tasks of a business process is critical. An empirical study conducted by Mitchell and Zmud (1999) using data from forty-three process-redesign projects in the health care industry, found that project performance improved when IT and work-process strategies were tightly coupled together.

Recent work in Information Systems includes work from the standpoint of process modeling (Basu and Kumar, 2002), process data reliability (Krishnan et al., 2005), implementation of processes using technologies for workflow management (Basu and Kumar, 2002; Kumar and Zhao, 2002; van der Aalst et al., 2003) and on process-centric design of information systems using technologies that permit orchestration of web services (Chakraborty and Lei, 2004). van der Aalst (2002) presented Petri nets as a tool for BP management. Bernstein et al. (1999) developed a tool for generating new business process ideas by recombining elements from a richly structured repository of knowledge about business processes. They demonstrate in their work that such a repository can be used automatically to generate a wide range of innovative process designs. Smith and Fingar (2003) argue that process-centric thinking can mitigate the business-IT divide and reduce the lag between management intent and execution. zur Muehlen and Rosemann (2005) present a taxonomy of process-related risks and discuss how this taxonomy can be applied in the analysis and documentation of business processes. They demonstrate how such process modeling methods as Architecture of Integrated Information Systems (ARIS) and extensions of the embedded Event-driven Process Chain Notation (EPCs) can be extended to document process-related risks and their relationships. Our work contributes to this literature by focusing on risk management issues related to data errors, in business process design problems.

Literature On Risk Management Minimizing expected loss is a satisfactory objective in applications when the loss can be viewed as normally distributed with a fixed standard deviation. Expected loss has been a widely used as risk measure for managing risks in many disciplines. In cases where the loss distribution is skewed, minimizing the expected loss is inadequate. We consider an alternative risk measure, *Value-at-Risk* (VaR) and *Conditional Value-at-Risk* (CVaR), in our risk management and optimal control structure-design model. The objective in using Value-at-Risk and Conditional Value-at-Risk measurement is to manage the risk of high losses. In order to define the Conditional Value-at-Risk, we first review the concept of *Value-at-Risk* (VaR). Value-at-risk (VaR) was devised by the Risk Metric group of the J.P.Morgan company (Morgan, 1996) as a methodology for credit risk assessment. Since then VaR has become a widely used measure for market risk associated with an asset or a portfolio of assets (Duffie and Pan, 1997; Jorion, 2003). VaR, in a financial context, is an estimate of the maximum potential loss with a certain confidence level, which a dealer or an end-user of financial instruments would experience during a standardized period. However, VaR does not provide any information about the amount of loss exceeding VaR. On the other hand, mathematically, VaR has some serious limitations. For example, in the case of a finite number of scenarios, it is a nonsmooth, nonconvex, and multiextremum function with respect to positions (Mausser and Rosen, 1998; Duffie and Singleton, 2003). Given these characteristics, solving an optimization with a VAR objective is difficult. Conditional Value-at-Risk (CVaR) has recently been suggested as an alternative risk measure. CVaR quickly gained popularity because it has some desirable properties that VaR does not have. Rockafellar and Uryasev (2000) gives a definition of CVaR that has been adopted by other researchers. Acerbi (2002) gives a representation of CVaR in terms of an average VaRand has demonstrated such important properties as the asymptotical convergence of statistical estimates to CVaR. CVaR is also proved by Pflug (2000) to be a sub-additive measure of risk compared with VaR, which is not sub-addtive. CVaR is also shown to be a coherent measure (Rockafellar and Uryasev, 2000; Pflug, 2000). Further, CVaR is a convex function under quite general assumptions (Acerbi, 2002; Rockafellar and Uryasev, 2002). Therefore computationally, for continuous distributions, CVaR-optimization leads to convex programming problems. For a finite discrete distribution, the optimal solution can be computed by solving linear programming (LP) problems. Beside its applications to finance, CVaR measure has gained increasing attention in other application areas, including facilities location problems (Chen et al., 2005).

3 Business Processes (BP) as a Graph

For different modeling purposes, processes can be represented in different ways. Our study focuses on the information flow perspective of a business process through graphical representation. A great deal of literature on graph-based models of business processes exists. Basu and Blanning (1994, 1998) proposed *metagraphs*, and demonstrated their flexibility for modeling processes, workflows, and decision-support resources (Basu and Kumar, 2002). Zhao et al. (2000) proposed a workflow-centric approach for organizational information distribution. Kumar and Zhao (1999) described a general framework for implementing dynamic routing and control mechanisms in workflow management. There is also literature that emphasizes well-formed workflows and analyzes their properties using Petri net models (Russell et al., 2005). In this section, we introduce our graphical modeling representation of a process. The notation we use throughout the paper is briefly summarized in Table 1.

Table 1: Descriptions of the notation used in the paper.

Parameters	Symbol	Description
Process topology	T	the *Task Precedence* matrix. T is a binary matrix of size $(N \times N)$. Its generic element $t_{ij} = 1$ if task i directly precedes task j. i, j: the task indices. N = the number of tasks in a process
	Γ	the *error propagation (EP)* matrix.
	γ_{ij}	the propagation potential of task i to task j. γ_{ij} is the entry at the i-th row and j-th column of Γ.
Information flow	$\vec{u}$	a single information unit in the business process.
Errors	$\mathcal{E}$	the set of the error types that can possibly occur in a process, $\lvert\mathcal{E}\rvert = M$.
	m	the single error types: $m \in \mathcal{E}$.
	$\tilde{e}_{im}$	random binary variable: the presence or absence of an error of type m created by task i.
	e_{im}	random variable: the number of errors of type m at task i.
Error distribution	$\vec{p}_i$	a M-dimensional random vector of the probabilities of the M types of errors being introduced by task i. $\vec{p}_i = (p_{i1}, \ldots, p_{iM})'$.
	p_{im}	the probability of an error of type m being introduced by task i .
Controls	x_i	the control utilization level at task i : $0 \leq x_i \leq 1$.
	$\alpha_i(x_i)$	the *effectiveness* function of a control procedure at task i .
Cost factors	c_{im}	the unit loss of an error of type m in an information unit at task i.
	$\omega_i(x_i)$	the cost of applying controls to task i.
Risk management	l_{im}	the monetary loss of task i introducing an error of type m to an information unit.
	$r_\beta(x)$	the Value-at-Risk at the significance level β
	$\phi_\beta(x)$	the conditional Value-at-Risk at the significance level β
	R	the total risk associated with data errors in the business process.

The BP Topology A business process model represents the flow of physical items or informational artifacts through a sequence of tasks and sub-processes that operate them. The flow may be directed by different types of *gateways* that can diverge or converge flows using such constructs as branches, forks, merges, and joins. These elements form a directed graph with the tasks as nodes and the gateways as arcs. A stylized graphical model of a business process

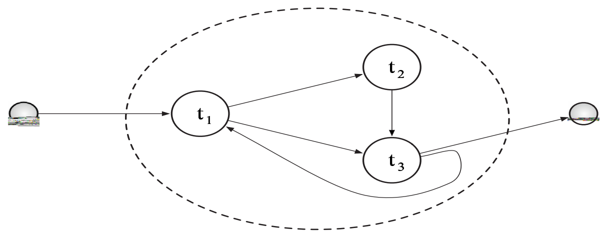

Figure 1: A graph representation of a business process consisting of information sources (the gray node at the starting point), error sources, and information repositories (the gray node at the end point) .

is shown in Figure 1. Each node in the graph represents a task. A directed arc from task 1 to task 2 implies that task 1 precedes task 2. The graph may be cyclic as well as hierarchical, where one of the nodes could be a sub-process containing its own directed graph. Further, directed arcs convey the exchange of information units between the tasks. Among the set of nodes that represent the tasks involved in a process, we identify two special sets to which we refer as *information sources* (the gray node at the starting point) and *information repositories* (the gray node at the end point). An information source is an origination point of data flows. It may be the starting event or initial task in a process. Consider the example of an order management process: The information source is a client's action of placing an order. Information repositories represent locations (real or virtual) where the data can be stored and retrieved. An example of this is a database containing business and financial data that is used by the company for decision-making, for the evaluation of its strategy, or for the generation of quarterly and annual financial reports to external parties including shareholders and regulatory agencies. Information sources and information repositories represent *interfaces* to the business process in that information is fed to the process via sources and delivered to other processes via repositories. Tasks operate on the incoming information flows, and may introduce errors. The set of nodes that represent such tasks are called *error sources*. The precise definition of *error* is given in Section 3.

This simple graph is extended to permit attributes of the nodes and the arcs – for example, the probabilities of certain type of errors being introduced by the tasks, – and the types of gateways. Later, when control systems are introduced, the model is further extended to include attributes of control procedures at each task location. For the sake of exposition, we will represent the business process topology and its associated attributes as a set of matrices and vectors through the rest of our paper.

Let T be the *precedence* matrix. T is a binary matrix of size $(N \times N)$ such that its generic element $t_{ij} = 1$ if task i directly precedes task j, and 0 otherwise. T encodes the topological structure of the process, and provides a map of paths of the information flows in the process. For example, the "1"s in the i-th row of T identify the set of the tasks that task i directly precedes. On the other hand, they imply that the information flow coming out of task i is fed to the set of tasks that directly follow task i. The information flow patterns such as convergence, divergence and feedback can be constructed using this basic matrix representation.

Information Flow in BP The information flow in the process is conceptualized as the flow of information units. Typically, an information unit is multi-dimensional. Consider our order fulfillment process example in an online pharmacy, where the information units in the process correspond to the orders for medication originating from the clients. The information contained in each order has several dimensions, including the patient demographic information, the patient history information, the patient credit history information, and the prescription information. The data in any one dimension of an information unit can get corrupted or lost. For example, the titration or strength of the medication or the number of refills could be recorded incorrectly. We refer to such incorrect missing or spurious data in an information unit as an *error*. As a starting point, we treat different dimensions equivalently from a risk perspective. Yet this constraint can be easily relaxed. Suppose an information unit is originated from an information source. The data content of the information unit may change at each step of the process. Errors are potentially introduced during the flow from a source to a repository. Later, we introduce controls that can be placed at each task capable of stochastically detecting and correcting errors. Such controls may further affect the data content. Information units eventually reach an information repository. Units in the repositories are used to generate *reports* for an organization's internal or external purposes, such as the key performance indicators (KPIs).

4 The Error Model

As discussed above, tasks may introduce errors to the information flow. Errors may be caused by a number of reasons including mistakes, omissions, delays, software glitches, and fraud. The probabilities of errors being introduced vary from task to task due to the heterogeneity of operations and the sources they involve. One task can sometimes introduce several types of errors. We discuss the error types we encountered in working with a functioning online pharmacy in Section 7. Furthermore, errors of different types are typically correlated at the same task since they are created by the operational resources for a common operational task. For example, for tasks that are operated by humans, the probabilities of errors being introduced are in general higher over all error types than the automated tasks.

Let p_{im} be the probability of the occurrence of errors of type m generated by task i. In the pharmaceutical case study in Section 7, and in many other applications, the p_{im} is either given or can be estimated from historical data. As a starting, the risk analysis in this study is conditional on the knowledge of a given set: $\{p_{im}\}$. In cases where $\{p_{im}\}$ are not exogenously given, they may be estimated using historical data. Generating of a set of probability vectors with a given correlation structure is of interest in and of itself. For example, it is useful for simulating and analyzing artificial corporate settings, making predictions, and simulating what-if scenarios. While we do not address this topic in this paper, our approach can work with probability density functions that are empirically or theoretically derived. Let $\tilde{e}_{im}$ denote the occurrence of errors of type m generated by task i. $\tilde{e}_{im}$ is assumed to follow a Bernoulli distribution with parameter p_{im}.

Path Relations and Error Propagation Errors introduced by tasks are propagated along paths in the process graph. We assume that if an error is generated at task i, it will be carried along to the succeeding tasks of i, unless it is detected and fixed by controls. The error propagation model is specified as follows: Let $p(T)$ be the $N \times N$ *volume transition* matrix of information flow. Each element of $p(T)$, $p(t_{ij})$ only represents the portion of the information flow that is coming out of task i and fed into task j. For example, in the case of order fulfillment process, $p(t_{ij}) = 1$ means that all of the orders coming out of task i are sent to task j; $p(t_{ij}) = 0.5$ means that half of the orders coming out of task i go to task j.

The expected sum of the adjacency matrices,

$$\Gamma = \sum_{k=1}^{K} p(T)^k \tag{1}$$

Γ is a matrix in which each cell, γ_{ij}, represents the ratio of the volume that is transmitted from one task to another (K represents the length of the longest path in the process graph). We call Γ the *error propagation* matrix. γ_{ij} is used to measure the impact of propagation of an error that arises in task i and propagates to its downstream task j. The hypothesis behind is that if one error arises at task i with probability p_{im}, γ_{ij} copies of the error will be transmitted to task j, which can be reached from task i. We call γ_{ij} the task i's *propagation potential* to task j. The computational complexity of computing γ_{ij} is $O\left(KN^2\right)$.

5 The Control Model

Controls provide a means to mitigate risk. In auditing, control procedures are categorized into preventative, detective and corrective controls (Wand and Weber, 1989; Spires, 1991). In typical BP settings, many different types of controls are used at various locations to assure process performances. Control examples include the information processing controls, physical controls, segregation of duties (SOD), and business performance reviews. Controls can be manual or automated. A specific type of control is designed to find and fix a specific set of error types. Combinations of many types of controls working together may be able to cover all the possible errors types and eventually achieve risk mitigation.

For our purposes, we abstract the characteristics of different types and consider controls as classifiers that detect and correct errors. [1] We treat controls as a pooled resource. Allocations are made from this pooled resource to each

[1] An analysis that retains the identity of the type of the error and of the controls to address these types of error involves a probabilistic set covering formulation which is the beyond the scope of this paper. The abstraction we employ permits an analytical treatment allowing us to focus on the role that BP structure plays in risk assessment and mitigation

task location, with larger allocations indicating larger investments in controls at that location. Further, controls can be applied at different levels of utilization (i.e. effort) that have associated cost, and error-detection implications. A concrete example of a control and its utilization is the sampling of such business documents as purchase orders, receiving reports, and invoices to detect valuation, existence, and completeness errors. The larger the sample size chosen, the greater is the cost to execute the control and the more likely the errors will be caught.

Error Detection Capabilities and Effectiveness of Control Suppose we have a set of control units available for use in a process. A control unit is deemed applicable if it has the capacity to fix errors that might arise at a task. Every task has a set of available control units to monitor and correct the performance of a task. Each control unit has its utilization capacity, which may or may not be fully put to use. Combinations of the control units along with their utilization levels represents a certain level of *control effectiveness*. The control effectiveness is measured by the error reduction rate of the control system when applied to a task.

Relating Control Effectiveness to Utilization Assuming the effectiveness of control depends on how much control is put into use (i.e. refer our sampling example) and false alarms only induce additional costs not additional errors to the information flow, the control effectiveness α is a function of the utilization level of control at each task: $0 \leq x_i \leq 1$, where $i \in \{1, \dots, N\}$. For example, $x_i = 0$ means that there is no control at a task i; $x_i = 1$ means that all available controls are applied at task i; and $0 < x_i < 1$ means that a portion x_i of the controls are applied at task i. Let $x = [x_1, ..., x_N]^T$ denote the decision vector that is to be chosen from the set of X of $\mathbb{R}^n$. The decision vector x represents a control allocation strategy at the process level from the set of available strategies X, subject to specific constraints. The x_is satisfy the constraint

$$\sum_{i=1}^{N} x_i \leq 1, \quad 0 \leq x_i \leq 1.\text{[2]} \tag{2}$$

The forms of $\alpha_i(x_i)$ may be specified according to the application context. In this paper, α is formulated as power functions of x_i with the power a between 0 and 1 scaled by a parameter g_i for task i. g_i represents the maximum effectiveness at which a control can perform at task i:

$$\alpha_i(x_i) = g_i x_i^{a_i}, \quad 0 < a_i < 1.\text{[3]} \tag{3}$$

Relating Control Costs to Utilization Extending the approach made by Krishnan et al. (2005), we require the cost of control to be a function of the control utilization factor. Let $\omega_i(x_i)$ be the cost of applying control to task i. We impose the most commonly used conditions for cost functions from system engineering (Kuo et al., 2001): $\omega_i(x_i)$ is a continuous, nonnegative, convex, and non-decreasing function of x_i. We assume that the average cost of catching errors in the information flow is lower at a task with a high *indegree*. The intuition is that by collecting information coming from multiple sources, it is easier for a control to detect errors. Hence, the average cost for a control to check a single transaction at task i, $\omega_i(x_i)$, is specified as a power function of x_i scaled by an in-degree parameter for task i:

$$\omega_i(x_i) = \frac{d_i \cdot x_i^{b_i}}{\hat{t}_i}, \quad b_i \geq 1, \quad d_i \geq 0. \tag{4}$$

where $\hat{t}_i = \sum_{j=1}^{N} t_{ji} p(t_{ji})$ is the product of value of t_{ji} (the entry at the jth row and ith column in the adjacency matrix ($\mathbf{T}$) weighed by $p(t_{ji})$ (the volume transition factor between task j and i).

6 Risk Measurement and Management

We consider three risk measures for optimal control design models: the *Expected Loss*, *Value-at-Risk*, and *Conditional Value-at-Risk*. Minimizing the Expected Loss is a satisfactory objective in applications in which the loss can be viewed as normally distributed with a fixed standard deviation. As a matter of fact, the Expected Loss has been a widely used measure for risk management in many disciplines.

[2]Our discussions with an online pharmacy management indicate that this is a reasonable assumption.

[3]As a starting point, we assume controls are equally effective for catching all types of errors. This assumption can be relaxed.

Expected Loss Assuming the occurrence of errors follows a Bernoulli trail, $\tilde{e}_{im}|p_{im} \sim Bernoulli\ (p_{im})$ ($m \in 1, \ldots M$ is the error type), the expected number of the errors of type m at task i

$$\bar{e}_{im} = \sum_{pathwaysinto(i)} (\sum_{j:inapathway(i)} \gamma_{ji} p_{jm}) + p_{im}, \tag{5}$$

then Equation 5 can be rewritten as

$$\bar{e}_{im} = p_{im} + \sum_{j=1}^{N} \gamma_{ji} p_{jm}. \tag{6}$$

By applying controls at task i, the number of errors reduced at task i is

$$\bar{e'}_{im} = (p_{im} + \sum_{j=1}^{N} \gamma_{ji} p_{jm}) g_i x_i^{a_i}. \tag{7}$$

The errors, if not caught, will propagate through the downstream tasks of the process, and incur certain business costs because the tasks are operated on incorrect information. The cost reduced is registered as the potential loss avoided:

$$\Delta l_{im} = (p_{im} c_{im} + \sum_{j=1}^{N} \gamma_{ji} p_{jm} c_{jm}) g_i x_i^{a_i} (1 + \sum_{j=1}^{N} \gamma_{ik}). \tag{8}$$

The benefit of applying control for a company is the expected loss reduction by reducing the error rates of tasks. It is measured as

$$\Delta L = \sum_{i=1}^{N} \sum_{m=1}^{M} \left((p_{im} c_{im} + \sum_{j=1}^{N} \gamma_{ji} p_{jm} c_{jm}) g_i x_i^{a_i} (1 + \sum_{k=1}^{N} \gamma_{ik}) \right) \tag{9}$$

Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) As noted above, minimizing the expected loss is a satisfactory objective only in applications in which the loss can be viewed as normally distributed with a fixed standard deviation. In cases where the loss distribution is skewed, optimization by minimizing the expected loss is inadequate. In the context of loss associated with error rates in the information flows in business processes, the loss distributions are, in general, skewed. Losses due to certain types of errors may be negligible, but may for other types be substantial. On the other hand, the loss associated with errors beyond a threshold may be significantly larger than that associated with errors below the threshold. In order to address these modeling challenges, we consider in this section two alternative risk measurement – *Value-at-Risk* (VaR) and *Conditional Value-at-Risk* (CVaR) – in our optimal control structure design model formulation.

Background Knowledge: β-VaR and β-CVaR Let f denote the probability distribution function of the loss. When the loss is continuous, f denotes the the probability density function; when the loss takes discrete values, f denotes the probability mass function. Similarly, we use $f(l|x)$ to denote the loss distribution function of l for a given decision vector x. The cumulative distribution function of loss for a given x, $\Psi(l|x)$, is defined as

$$\Psi(l|x) = \int_{-\infty}^{l} f(z|x) dz. \tag{10}$$

Value at risk (VaR) at a significance level β for a given x, $r_\beta(x)$, is:

$$r_\beta(x) = \min_{l} \left\{ \ l \in \mathbb{R} \ : \ \Psi(x, l) \geq \beta \ \right\}. \tag{11}$$

The CVaR at a significance level β is called *β-CVaR*. The value of the β-CVaR of a loss associated with a decision x is essentially the mean of the β-tail distribution of $\Psi(l|x)$, which we denote as $f_{z \geq r_\beta(x)}(z|x)$. The average loss in the tail is:

$$\phi_\beta(x) = \frac{1}{1-\beta}\int_{r_\beta(x)}^{+\infty} f(z|x)dz \tag{12}$$

$\phi_\beta(x)$ denotes the value of the β-CVaR. Rockafellar and Uryasev (2000) showed that the β-CVaR value for the loss random variable associated with x can be determined from the formula

$$\phi_\beta(x) = \min_{r\in\mathbb{R}} F_\beta(x,r), \tag{13}$$

where

$$F_\beta(x,r) = r + (1-\beta)^{-1}\int_{z\in\mathbb{R}} [f(z|x) - r]^+ dz \tag{14}$$

Designing Optimal Control Procedures The optimal design of the control structure is the design that maximizes the net benefit of applying controls. In this section, we formulate three optimization problems, the "Expected-Loss-Optimal" model, which finds the optimal control structure by minimizing the expected loss; the "β-VaR-Optimal" structure, which finds the optimal control structure by minimizing the VaR at the β significance level; and the "β-CVaR-Optimal" structure, which finds the optimal control structure by minimizing the CVaR at the β significance level:

$$\begin{aligned} \max \quad & R - \sum_{i=1}^{N} \omega_i(x_i) \qquad (15) \\ \text{s.t.} \quad & \sum_{i=1}^{N} \omega_i(x_i) \le B; \sum_{i=1}^{N} x_i \le 1; 0 \le x_i \le 1;\ i = 1, ...N \end{aligned}$$

where $R = \Delta L$ for the "Expected-Loss-Optimal" formulation; $R = r_\beta(x)$ for the "β-VaR-Optimal" formulation; and $R = \phi_\beta(x)$ for the "β-CVaR-Optimal" formulation.

7 Case Study: Pharmacy Order Fulfillment Process

We collected the data from a medium-sized online pharmacy that provides both pharmacy services and pharmaceutical information system management services. In this section, we illustrate the preliminary application of our risk management model to the order fulfillment process at this firm.

Figure 2 shows the high-level business process model diagram. The process begins with the clients/patients ordering medication, and ends with the pharmacy recognizing revenue. After an order arrives at the pharmacy, it is sent to the order management center. At the order management center, the order is processed and relevant contrasts are updated. The valid orders are then sent to the in-house pharmacies where the orders are fulfilled. The bills are sent out from the billing management center to the insurance companies or the clients/patients. At the same time, the medicines are delivered from the in-house pharmacies by contracted carriers to the clients/patients. The payments are collected at the end of each month at the billing center and recognized as revenue at the accounting department. Each management center is a module that contains a subprocess. Within the subprocess, sequences of tasks are performed to achieve the function of the module. The company interacts with other parties including clients, drug manufacturers, and insurance companies. Controls in our study focus on intra-organizational tasks.

Tasks and Information Flow The order of medication is the information flow in the order fulfillment process. The order of medication flows through the following tasks as shown in the diagram: 0) nurses/Doctors enter patient order information; 1) stuff enter patient/order information into QS1 system; 2) stuff enter patients payer information and check for insurance; 3) stuff create/update contracts; 4) pharmacist approves prescriptions; 5) orders are sent to FDS/EXP dispensing system for dispensing or filled as a bulk item; 6) out of stock medicine need to be obtained from alternate source for dispensing; 7) daily drug order is submitted to wholesaler; 8) medicines are sorted by facility

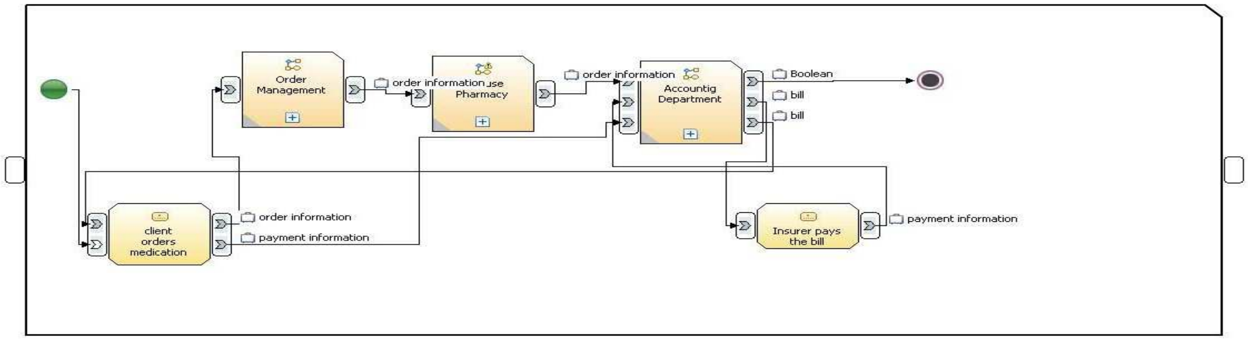

Figure 2: The high-level process model diagram of the order fulfillment process.

and placed in totes for delivery along with a manifest; 9) a claim, if applicable, is sent to insurance companies; 10) should a claim not be applicable, charges are entered on the bill sent to the patients' respective responsible parties; 11) payments are received from responsible parties and insurance companies; 12) payments are posted to QS1 system, voucher package is prepared; 13) end of month financial reports are run (a.k.a. updating ledgers); 14) insurance companies or clients pay bills. Fifteen tasks are involved to fulfill the order. The scope of the process involves two external players: the clients or patients, and insurance companies. task 0) interacts with clients or patients; task 14) interacts with insurance companies. These two tasks are not considered as locations where the pharmacy can apply controls. Our model focuses on designing optimal control allocations at the thirteen internal tasks. The maximum number of steps in the process is eleven.

Model calibration on process topology First, we represent the process network using task precedence matrix ($\mathbf{T}$) and volume transition matrix ($p(\mathbf{T})$); then we calculate the propagation impact matrix (Γ). The *volume transition* matrix $p(\mathbf{T})$ for the complete process is calibrated as follows

$$p(\mathbf{T}) = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & .9 & .1 & .1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & .8 & .2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix},$$

and the resulting the *propagation impact* matrix Γ is calibrated as follows

$$
\Gamma = \begin{bmatrix}
0 & 11 & 21 & 19 & 17 & 13.5 & 1.5 & 1.5 & 14.3 & 14.3 & 24.2 & 19.8 & 15.4 \\
0 & 0 & 11 & 10 & 9 & 7.2 & 0.8 & 0.8 & 7.7 & 7.7 & 13.2 & 11 & 8.8 \\
0 & 0 & 0 & 11 & 10 & 8.1 & 0.9 & 0.9 & 8.8 & 8.8 & 15.4 & 13.2 & 11 \\
0 & 0 & 0 & 0 & 11 & 9 & 1 & 1 & 9.9 & 9.9 & 17.6 & 15.4 & 13.2 \\
0 & 0 & 0 & 0 & 0 & 9.9 & 1.1 & 1.1 & 11 & 11 & 19.8 & 17.6 & 15.4 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 11 & 11 & 20 & 18 & 16 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 11 & 11 & 20 & 18 & 16 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 11 & 11 & 20 & 18 & 16 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 11 & 10 & 9 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 11 & 10 & 9 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 11 & 10 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 11 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
$$

Model calibration on occurrence and cost of errors We collected data on 47 different errors that occurred in the order fulfillment process at the pharmacy, including the respective costs and frequencies of occurrences of errors.[4] The data provides the average cost per error per type ($\hat{c}_{im}$) and the frequency of error occurrences on a monthly basis. Note that the errors of different types occur following a Bernoulli distribution $\tilde{e}_{im}|p_{im} \sim Bernoulli\ (p_{im})$ trail. We use the frequency of error occurrences to calculate $\hat{p}_{im}$, which is then used to sample error instances ($\tilde{e}_{im}$) in the numerical procedures.

Table 2: The cost factors of controls at each task and the parameter estimates.

Task	The cost factors (/hr/person)	Estimates (d_i, b_i)
1, 2, 3, 9	\$ 20/hr/person for trainees * 30 hr/person/month; \$ 40/hr/person for the trainers * 3 hr/person/month; \$ 50/hr/person of IT setup * 3 hr/person/month.	(870, 1)
4	\$ 40/hr/person for trainees * 30 hr/person/month; \$ 160/hr/person for the trainers 3 hr/person/month;	(1680, 1)
5,6,7,8,10,11	\$ 20/hr/person for trainees * 30 hr/person/month; \$ 40/hr/person for the trainers 3 hr/person/month.	(720, 1)
12, 13	\$ 40/hr/person for trainees * 30 hr/person/month; \$ 40/hr/person for the trainers 3 hr/person/month; \$ 100/hr/person of IT setup * 3 hr/person/month.	(1620, 1)

The matrix that represents the error probabilities p_{im} and the error costs c_{im} are calibrated as in Equation 7. In both matric, the first column represents *Accuracy*, the second column represents "Completeness", the third column represents *Existence*, the fourth column represents *Occurrence*, the fifth column represents *Rights & Obligations*, the sixth column represents *Classification*, and the the seventh column represents *Cutoff*. The rows represent task locations.

Control methods and Cost of Control The controls chosen by the pharmacy are used to train the employees to operate with less mistakes. The available methods to eliminate errors include 1) moving the message queue from intranet to *mPower*; 2) reviewing medication errors with the staff as part of training; 3) pharmacist checks of all medicine being put into the dispensing machine; 4) pharmacist checks of all medicine being put into the trays of the dispensing machines; 5) double checking the cycle fills by two different staff members; 6) random checks throughout the day of order entries; 7) checking the items on the delivery sheet against the items in the respective tote; 8) extra training for new hires; and 9) automated procurement systems to eliminate incorrect manufacturers being ordered. the

[4]A complete table of error information is available.

$$\{p_{im}\} = \begin{bmatrix} 2.0\% & .1\% & .5\% & 1\% & 0 & 0 & 0 \\ .3\% & 0 & 0 & .1\% & 0 & 0 & 0 \\ 0 & .1\% & 0 & .1\% & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & .2\% & 0 & 0 \\ .3\% & 0 & 0 & .1\% & 0 & 0 & 0 \\ .3\% & 0 & 0 & .1\% & 0 & 0 & 0 \\ .02\% & 0 & 0 & & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & .5\% & 0 \\ .2\% & .5\% & 0 & 0 & 0 & 0 & 0 \\ 7.5\% & .2\% & .02\% & 0 & 0 & 0 & 0 \\ .02\% & 0 & 0 & .02\% & 0 & 0 & 0 \\ 0 & .1\% & .1\% & 0 & 0 & .1\% & 0 \\ .1\% & 0 & 0 & 0 & 0 & .1\% & .1\% \end{bmatrix}; \quad \{c_{im}\} = \begin{bmatrix} 250 & 100 & 100 & 100 & 0 & 0 & 0 \\ 100 & 0 & 0 & 250 & 0 & 0 & 0 \\ 0 & 100 & 0 & 250 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 500 & 0 & 0 \\ 100 & 0 & 0 & 100 & 0 & 0 & 0 \\ 100 & 0 & 0 & 100 & 0 & 0 & 0 \\ 1000 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 40 & 0 \\ 100 & 50 & 0 & 0 & 0 & 0 & 0 \\ 30 & 50 & 2500 & 0 & 0 & 0 & 0 \\ 1000 & 0 & 0 & 25 & 0 & 0 & 0 \\ 0 & 25 & 25 & 0 & 0 & 25 & 0 \\ 25 & 0 & 0 & 0 & 0 & 25 & 50 \end{bmatrix}.$$

Figure 3: The error probabilities (p_{im}) and error costs (c_{im}), $i = 1, ...13$ and $m = 1, ...7$.

data on the cost of extra training we received includes \$20 per hr for the cost of the trainer, \$40 per hr for the cost of IT to set up the equipment needed and \$50 to \$100 per hr for the pharmacy staff being trained.

Model calibration on cost and effectiveness of controls Better-trained employees are assumed to perform their tasks more effectively at their respective tasks, i.e., a_i is consistent over i. Table 2 lists the cost factors of the controls provided by the pharmacy. The empirical estimates that the maximum effectiveness of the extra training on stuff member can be achieved is

$$g_1 = \quad ... \quad = g_{13} = 1 \tag{16}$$
$$a_1 = \quad ... \quad = a_{13} = 0.5, \tag{17}$$

where $g_1 = ... = g_{13} = 1$ implies that through proper training and the best possible control performance, all errors can be caught and corrected right where they are generated. $a_1 = ... = a_{13} = 0.5$ implies the diminishing marginal effectiveness of control. Having calibrated the parameters of our model, we present in the next section the computational results.

7.1 Computational Results

The transaction history for 12,000 orders of medication (informational units) were simulated using the data on topology, error probabilities, and costs provided by an online pharmacy. By performing this simulation we were able to abstract the order fulfillment process, and to estimate the risk exposure *ex ante* of the impact of the order management process under optimal control strategies.

Control strategy	Amount of control allocated at individual BP tasks														
	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	In	Out
No Control	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Random	0.04	0.12	0.08	0.09	0.11	0.08	0.10	0.01	0.12	0.05	0.10	0.11	0.02	0.00	0.00
Prop. to $\vec{p}$	0.24	0.03	0.01	0.01	0.03	0.03	0.03	0.03	0.05	0.51	0.00	0.02	0.01	0.00	0.00
Prop. to $\vec{\gamma}$	0.31	0.15	0.15	0.14	0.04	0.04	0.04	0.04	0.03	0.01	0.01	0.01	0.00	0.00	0.00
Bai 07, analytical	0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.50	0.34	0.00	0.00	0.00	0.00	0.00
Bai 07, min Loss	0.58	0.00	0.00	0.12	0.00	0.00	0.00	0.00	0.01	0.02	0.00	0.00	0.26	0.00	0.00
Bai 07, min VaR	0.59	0.08	0.00	0.00	0.00	0.00	0.00	0.03	0.08	0.03	0.00	0.00	0.18	0.00	0.00
Bai 07, min c-VaR	0.75	0.00	0.00	0.19	0.00	0.00	0.00	0.02	0.03	0.00	0.00	0.00	0.00	0.00	0.00

Table 3: Task-specific control allocations suggested by different strategies for the order fulfillment process topology.

We observed from the results in Table 3 and 4 that the optimal levels of control allocation are positively correlated to the costs and effectiveness of the controls. The optimal strategy for the pharmacy is to choose to apply more control

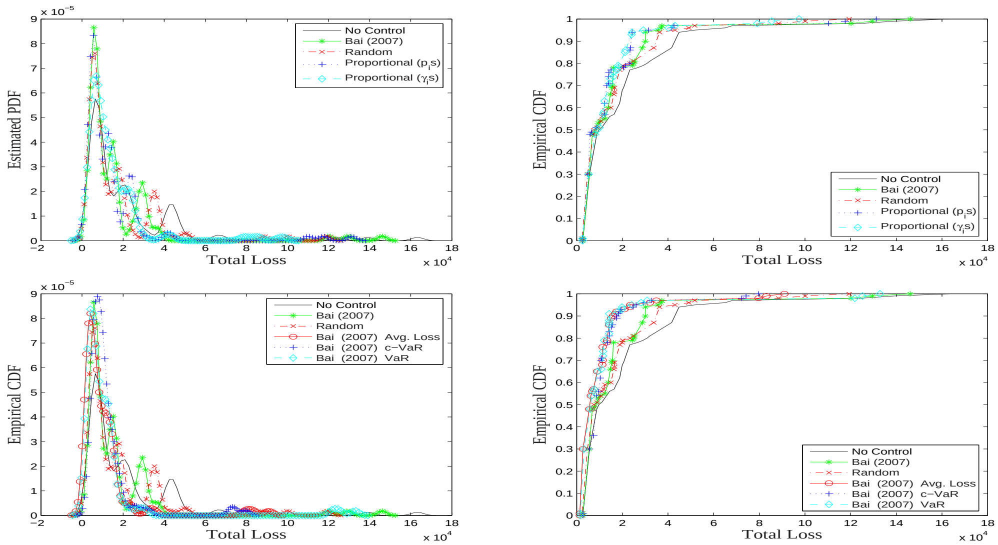

Figure 4: Top: the topology for the order fulfillment process. Middle left: the pdfs of loss distribution of the benchmark strategies. Middle right: the corresponding cdfs of loss distribution under the control strategies. Bottom left: pdfs of loss distribution using different risk objectives. Bottom right: the corresponding cdfs of loss distribution using different risk objectives.

resources where it is more effective or less expensive. For example, the tasks “enter order/patient information” and “prove prescription” have been allocated with high levels of control effort in most strategies. This result confirms our argument that the optimal level of controls is proportional to the frequency of error occurrence and the magnitude of the consequence if an error occurs. We make the following four observations:

Observation 1 The effort invested in control at a task is proportional to the frequency of the error occurrence and the magnitude of the consequence (cost of errors) if an error occurs. As the error frequency or the unit cost of an error increases, the amount of control resources applied increases. The results in Table 3 shows that task 1), “staff enter patient/order information into QS1 system”, is constantly allocated to the largest amount of control effort because, compared with other tasks, it has the most types of errors, the frequency of occurrence of each type of error is among the highest, and the magnitude of the consequence of errors is significant as well.

Observation 2 Tasks that are earlier in the process are more critical because the errors generated have a greater impact on risks due to propagation. Thus holding other factors constant, it is optimal to apply control at tasks that are earlier in the process than later. This partially explains why task 1) is the most critical location in the process to apply controls.

Observation 3 The effort invested in control at a task is positively correlated to the connectivity of the task. This is intuitive because by applying control to the task that is on most of the pathways of a process, the control is more likely to detect errors and prevent them from being spread to the rest of the process. As shown in Table 3, task 4) “Pharmacist approves prescription,” has been allocated with control in all the optimization base strategies. the two downstream branching tasks of task 4),which are task 5) “Orders are sent to dispensing systems for dispensing” and task 6) “Out of stock medicine be obtained from alternate source for dispensing”, have no control applied in nearly all the optimal control allocations.

Observation 4 When the marginal effectiveness of each control is the same, the allocation of control effort is cost-effective to be invested in task locations where the cost of control is less expensive to apply. Notice that the amount of allocation at task 1) is significantly larger than that at task 4. This is partially because the cost of training a staff that can perform control task 1 is one-third less expensive than training a pharmacist to perform control at task 4.

Table 4 presents the resulting risk measures by different strategies for the order fulfillment process. The pattern shows the trade-offs in the resulting risk measures for each risk management objective. For example, if the pharmacy

Control strategy	Loss	VaR	c-VaR	Amount	Cost
No Control	21544.10	44840.00	137402.00	0.00	0.00
Random	16967.66	36312.89	106907.83	1.00	80.23
Prop. to $\vec{p}$	14886.10	24264.64	88736.02	1.00	243.17
Prop. to $\vec{\gamma}$	14336.46	24053.74	80755.90	1.00	163.79
Bai 07, analytical	16635.01	30068.92	92665.59	1.00	124.51
Bai 07, min Loss	10580.36	16324.55	58600.20	1.00	426.09
Bai 07, min VaR	11905.24	14203.79	70544.43	1.00	365.08
Bai 07, min c-VaR	12227.32	17949.76	57533.92	1.00	556.25

Table 4: Computational results by different strategies for the order fulfillment process topology.

wishes to minimize the expected loss due to errors in the transaction information flow, the “Expected-Loss-optimal” control strategy, which minimizes the expected loss plus the cost of applying control, results in the lowest Expected loss, but with a higher VaR ($\$1045.67$) than that of the strategy that aims to minimize VaR ($\$1005.68$), and a higher CVaR ($\$7828.06$) than that of the strategy that aims to minimize CVaR ($\$7740.72$). The “VaR-Optimal” solutions presented in Table 3 and 4 are not guaranteed to be the “global” optimal. Similar pattern applies to the “VaR-Optimal” and “CVaR-Optimal” strategies.

8 Concluding Remarks

This study has proposed a framework for identifying the control locations and amount of control effort at each location, in order to minimize the risk exposure of the BP under budget constraints at the process design phase. This framework establishes a risk-based approach to BP design that characterizes the impact of the errors in information flow to the risk exposure of a business process and develops control strategies to minimize the risk exposure. Our perspective of BP design is novel in the sense that we look at the risk aspect of a BP at the design phase. We argue that the structural aspect of the BP is the key to assessing and managing risks due to errors. Our model accounts for the process structure in error generation, propagation, and mitigation. In designing optimal control structures for a business process, we have applied three risk measures: Expected Loss, Value-at-Risk (VaR), and Conditional Value-at-Risk (CVaR). We demonstrate our method through an order fulfillment process in a functioning online pharmacy. Our model applies to various levels of organizational processes. Further, our model lends itself to implementation within process modeling workbenches offered by leading software vendors for both design and re-engineering purposes.

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